A Small, Portable, Battery-Powered Brain-Computer Interface System for Motor Rehabilitation

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***Abstract*— Motor rehabilitation using brain-computer interface (BCI) systems may facilitate functional recovery in individuals after stroke or spinal cord injury. Nevertheless, these systems are typically ill-suited for widespread adoption due to their size, cost, and complexity. In this paper, a small, portable, and extremely cost-efficient (<$200) BCI system has been developed using a custom electroencephalographic (EEG) amplifier array, and a commercial microcontroller and touchscreen. The system's performance was tested using a movement-related BCI task in 3 able-bodied subjects with minimal previous BCI experience. Specifically, subjects were instructed to alternate between relaxing and dorsiflexing their right foot, while their EEG was acquired and analyzed in real-time by the BCI system to decode their underlying movement state. The EEG signals acquired by the custom amplifier array were similar to those acquired by a commercial amplifier (maximum correlation coefficient ρ=0.85). During real-time BCI operation, the average correlation between instructional cues and decoded BCI states across all subjects (ρ=0.70) was comparable to that of full-size BCI systems. Small, portable, and inexpensive BCI systems such as the one reported here may promote a widespread adoption of BCI-based movement rehabilitation devices in stroke and spinal cord injury populations.**

I. INTRODUCTION

Millions of individuals in the US are afflicted by motor impairments caused by stroke and spinal cord injury (SCI) [1], [2], [3], [4], [5]. These impairments can lead to serious health problems and lost productivity for the affected individuals [1], [5]. Despite standard rehabilitative therapies, motor recovery in stroke and SCI survivors typically plateaus six months after injury [5], [6], [7]. However, recent studies suggest that the use of brain-computer interfaces (BCIs) in post-stroke movement therapy (assisted by a robot or electrical stimulation) may promote motor recovery [8], [9], [10], [11]. This approach could potentially be applied to SCI motor rehabilitation, as it has already been shown that BCIs can be used effectively by subjects with paraplegia and tetraplegia [12], [13].

Current BCI systems are not well-suited for use outside the clinic or research laboratory due to their size, cost, and lengthy setup time. This is problematic, since the general consensus in motor rehabilitation is that the best therapies are those that can be done often and at home [14]. For noninvasive BCIs to be a practical rehabilitative option, they must be readily available as small, portable, low-cost systems. These systems consist of electroencephalographic (EEG) amplifiers as well as a processing unit that translates brain signals into control commands for an output device. While commercial amplifier systems are available for purchase, they can be expensive and bulky. Additionally, both commercial and research amplifiers generally require a desktop or laptop computer [15], [16], [17] for signal processing. Thus, these BCI systems are neither small nor portable and require extensive setup. The few research BCI systems that can utilize an embedded processing unit for real-time BCI use are expensive, overly complex, or too bulky [18], [19]. In order to meet our goals (simple, compact, portable, and low-cost), we have designed and tested a BCI system for motor rehabilitation that utilizes a custom 4-channel EEG amplifier, a commercial microcontroller, and a touchscreen (see Fig. 1).

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II. METHODS

A. Hardware Design

A custom 4-channel EEG amplifier (Fig. 2) was designed, fabricated (Smart-Prototyping, NOA Labs, Kowloon, Hong Kong), and paired with an Arduino Mega microcontroller (Arduino, Ivrea, Italy) and touchscreen with on-board microSD card (Seeed Studio, Shenzhen, China). The entire system was supplied by a portable 5V battery. Each EEG channel of the amplifier array is comprised of an instrumentation amplifier followed by two operational amplifiers. This three-stage amplifier has a banded frequency response realized using built-in active high-pass (corner frequency of 1.59 Hz) and low-pass (corner frequencies of 33.86 Hz and 32.88 Hz, respectively) filters. The minimum total gain of the amplifier is 28704$\times$, with >80 dB common mode rejection ratio. Further common mode noise reduction is achieved by exploiting active shielding on the EEG cap (ANT Neuro, Enschede, Netherlands). To reduce the board size and production costs without compromising performance, only a subset of 4 EEG channels was used. Post-hoc analysis of our previous data [9], [12] suggests that BCI performance does not improve significantly for >4 channels (unpublished). To facilitate easy integration with the microcontroller and touchscreen, the amplifier array was designed to form a stack with these components. The entire assembly (see Fig. 1) is

Fig. 1. A picture of our BCI system with an EEG cap and a portable 5V battery. The BCI system and battery cost <\$200. The touchscreen, with built-in microSD slot, acts as the user-interface for the BCI system and eliminates the need for a monitor and keyboard. It snaps onto a shield with the custom amplifier array which snaps onto a commercial microcontroller. EEG signals are amplified by the custom array and sent directly to the microcontroller for processing, BCI decoding, and effector output.

small (7.5×10×3 cm) and costs less than \$200 (excluding the EEG cap).

B. Signal Acquisition

The University of California, Irvine Institutional Review Board approved the use of human subjects for this study. Three able-bodied subjects were fitted with a commercial 64-electrode EEG cap, and a combination of conductive gel and skin abrasion was used to reduce the impedances to <10 kΩ for electrodes Cz, CPz, C1, and C2 [20]. Note that these electrodes are expected to cover the foot motor areas. Signals were referenced to electrode AFz, and a bias electrode at M2 was used. To validate the fidelity of the custom amplifier array, EEG from electrode Cz was simultaneously acquired by both the custom array and a commercial amplifier EEG100C (BIOPAC Systems, Goleta, CA) at 4kHz sampling rate using an MP150 ADC (BIOPAC Systems, Goleta, CA). To match the filtering characteristics of our custom amplifier, signals from the commercial system were subjected to analogous software filters (high-pass at 1.59 Hz and low-pass at 33.86 and 32.88 Hz). Finally, the Pearson correlation between signals from both systems was calculated.

Subjects then underwent a 4-min BCI training session, in which they followed alternating 6 s cues on the touchscreen to relax or dorsiflex their right foot. EEG signals were sampled at 256 Hz per channel by the microcontroller. Next, these data were bandpass filtered in software to extract the α (8-12 Hz) and β (13-30 Hz) bands. The average power of the 8 output signals (4 channels x 2 frequency bands) during the last 5 s of each cue was calculated and stored on the microSD card. Note that this effectively eliminates from analysis a 1-s transition period. This training data (8 dimensions × 40 epochs) was then used to generate a classifier that could distinguish relaxing from dorsiflexing based on EEG data (based closely on [21]).

C. Classifier Design

First, principal component analysis was used to reduce the number of dimensions of the training data while ensuring that ≥99.7% of the overall variance was still explained. The resulting lower dimensional data was then subjected to linear discriminant analysis to find the 1-D projection that maximized class separability. The data in this optimal 1-D subspace was used to generate a Bayesian classifier that calculated the posterior probability of dorsiflexing (P_D). The overall projection vector and classifier parameters were stored on the microSD card for subsequent real-time BCI operation. Ten-fold cross-validation was also run on the Arduino board to estimate the accuracy of the classifier model.

A binary state machine using two thresholds, T_1 and T_2, translated P_D into one of two states: relaxing or dorsiflexing. If $P_D < T_1$, the system predicted the relaxed state; if $P_D > T_2$ (where $T_2 > T_1$), the system predicted the dorsiflexed state. Otherwise, the system defaulted to the last predicted state. These thresholds were determined using a 1-min calibration session, where P_D was calculated every

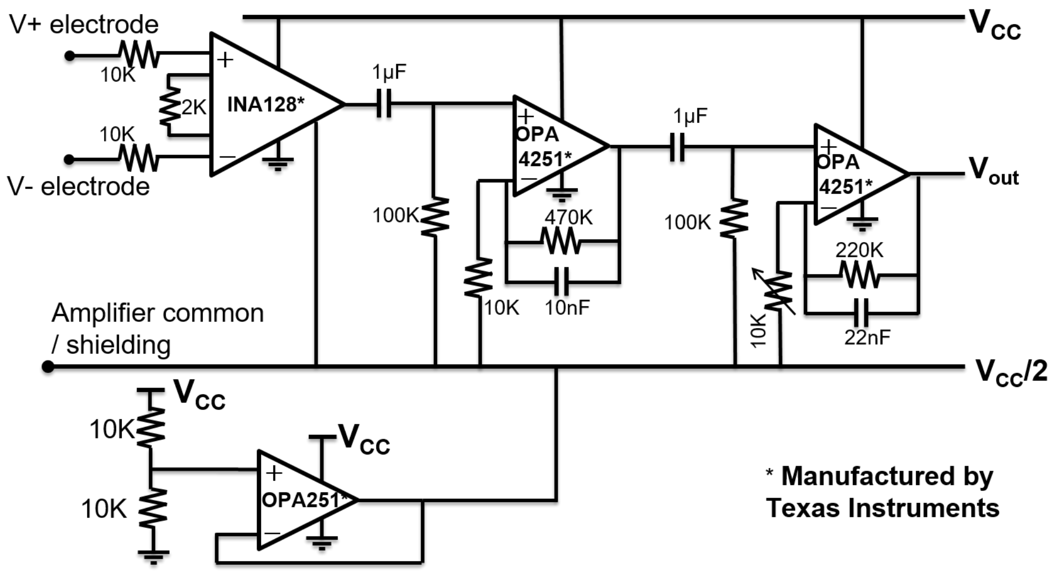

Fig. 2. The schematic of a single channel from the custom amplifier array. Note the presence of 3 amplifier stages with high-pass and low-pass filters. Environmental noise is further attenuated using active shielding. The 4-channel system was designed to stack onto the microcontroller.

0.5 s while subjects followed alternating 6-s cues to idle or dorsiflex their right foot. Using a grid search, T_1 and T_2 were chosen such that the accuracy of the predicted states was maximized.

D. Real-Time BCI Testing

Subjects participated in 2-3 trials (120 s each) where they followed alternating 6-s cues to relax or dorsiflex their foot. The BCI system analyzed their EEG signals using the subject-specific classifier generated above to predict the subject's movement state (relaxed or dorsiflexed) every 0.5 s. In order to prevent noisy state transitions, the mode of the last 3 predictions determined the final BCI output. Visual feedback was provided in the form of an LED that was controlled by the BCI output. The performance of the system was assessed as the correlation between the cues and BCI output.

III. Experimental Results

Three able-bodied subjects participated in this study (see Table I). The correlation between the custom and commercial amplifiers during a 50 s single-channel recording for S1, S2, and S3 was 0.85, 0.84, and 0.73 respectively. A representative 3-s example of EEG from S1 acquired by both systems is provided in Fig. 3. BCI decoding results for S1-3 are also provided in Table I. In addition, a representative example of S1's training data in the original 8-D and the final 1-D subspace is provided in Fig. 4. All the steps required for real-time decoding were performed by the microntroller using custom software. Note that despite the limited processing capacity of an Arduino Mega, classifier generation, cross-validation, and threshold calibration each took <20 s to perform.

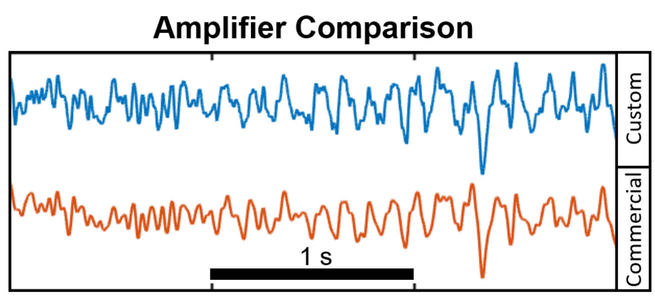

Fig. 3. A 3-s example of EEG data (electrode Cz) from S1 when amplified with the custom (blue) and commercial (red) amplifiers.

TABLE I

Summary of BCI testing results including the offline 10-fold cross-validation performance, number of online trials, and average correlation between instructional cues to relax/dorsiflex and decoded online BCI state.

Subject	Cross-Validation Accuracy	Number of Trials Completed	Average Cue-Output Correlation per Trial
S1	97.5%	2	0.82
S2	95%	3	0.63
S3	100%	2	0.63

IV. Discussion and Conclusions

A BCI system was implemented using a custom amplifier array, a commercial microcontroller, and touchscreen to decode movement-related EEG changes. Despite the disparate hardware characteristics of the custom and commercial amplifiers, the amplified EEG signals were similar. Moreover, the custom amplifier yielded EEG signals that were free of motion artifacts and environmental noise, and enabled accurate BCI decoding in 3 inexperienced able-bodied sub-

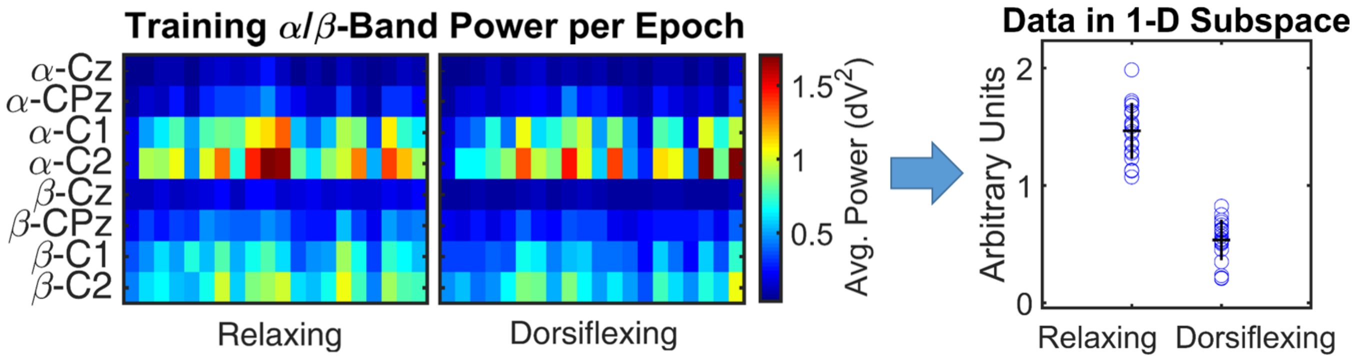

Fig. 4. Left: The original 8-D training data collected from S3 during 20 relaxing and 20 dorsiflexing epochs and stored on the microSD card. Right: The training data after it was projected by PCA and LDA onto the most-separable 1-D subspace. The mean (horizontal bar) and standard deviation (vertical bars) for each state is provided. Note that the training data from the relaxed and dorsiflexed states are highly separable in this 1-D subspace.

jects. The observed real-time decoding performances across subjects (average of ρ=0.70) were comparable to previous studies in able-bodied individuals [22] and stroke survivors [21] that utilized full-size BCI systems with longer training times and a significantly higher number of EEG channels. By utilizing only 4 EEG channels, setup time is greatly reduced, making this BCI system more appropriate for frequent, at-home use. Specifically, the setup time for this BCI system was $<$10 mins for all subjects. Note that a somewhat inferior performance of subject S3 could be explained by a larger-than-usual level of environmental noise that was observed during the subject's experiment.

In summary, we demonstrated that a small, simple, and inexpensive BCI system could accurately decode the movement state of 3 able-bodied users from EEG signals. We expect that this system can be used easily and effectively by both stroke and SCI survivors without significant loss of performance compared to expensive, full-size BCIs. Additionally, our BCI system can be paired with portable and cost-efficient end-effectors, such as commercial functional electrical stimulators, to produce a simple and accessible BCI-based movement therapy for stroke and SCI survivors. Future directions will include testing the system with motor-imagery-based control strategies, as well as in people with stroke and spinal cord injury.

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